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MACHINERY DIAGNOSTIC FEATURE EXTRACTION AND FUSION TECHNIQUES USING DIVERSE SOURCES

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Abstract: In order to optimize helicopter operational readiness a Joint Advanced Health and Usage Management System (JAHUMS) for helicopter must be highly reliable, minimize false alarms, and prevent catastrophic failures, while operating in real time. To achieve these goals, a fusion of features extracted from non-commensurate factors such as, vibration with oil temperature, oil pressure, and wear debris signatures was implemented via statistical fusion techniques.

This feature fusion of non-commensurate factors provides improved diagnoses capability and reduces false alarms. For example, there may be instances where one analysis factor indicates a fault while another has a contra indication. Clearly, fusion of non-commensurate features will be a very effective way to overcome these conflicts, thereby providing better diagnosis performance and improved flight safety of helicopters.

Another advantage of this feature fusion is significant data compression through dimensionless statistical discriminators, which is indispensable to efficient storage utilization and on-line real-time analysis. Therefore, data fusion of non-commensurate sources provides efficient machinery diagnosis and prognosis for both the military and commercial field.

Key words: Dimensionless discriminants; Feature extraction; Feature fusion; Machinery diagnostics; Normalization; Nominal/Anomalous diagnostic discriminator

Introduction: The JAHUMS operational system for helicopter must be highly reliable, minimize false alarms, and give sufficient advance warning to prevent catastrophic failures, while operating in real time, hence a high utilization rate for helicopter availability.

In order to achieve these goals, the fusion of features extracted from vibration signatures, with non-commensurate signatures derived from transmission oil temperature, transmission oil pressure, and wear debris was implemented via statistical fusion techniques. This fusion accomplishes nominal/anomalous diagnostic and prognostic health monitoring for JAHUMS. This idea fuses non-commensurate factors for JAHUMS, which provides increased diagnoses capabilities and reduces the number of false alarms. There

may be instances when one technique indicates a fault while another has a contra indication. For example, in applications where sliding wear is prevalent, chip detection might detect increasing rates of wear generation, while the vibration amplitude remains nominal. Another example, oil pressure and tail transmission oil temperature failure will not be detected by vibration features. Any anomalous condition indications could cause catastrophic failures. Therefore, features extracted from any single factor might not indicate an anomalous condition, whereas other feature co-factors may indicate an anomalous condition. Clearly, fusion of non-commensurate with vibration signatures provides better machine diagnosis performance and improved flight safety for helicopters.

Other distinguished features of JAHUMS system developed by AMTEC Corporation and Wyle Laboratories Incorporated are their data compression and dimensionless normalized features, which enables standardizing analysis regardless of helicopter torque or load conditions. This is achieved using normalized and dimensionless scaling transforms called statistical measures. Data compression is a must when sampling rates are high and data storage is limited. These techniques make real time and on-line a reality for JAHUMS.

Therefore, fusion techniques, which integrate data compression and dimensionless normalized features for the novelty detection of JAHUMS operational system provide a truly advanced and reliable, yet efficient machinery diagnosis and prognosis system for both military and commercial field.

Nominal/Anomalous Diagnostic Discriminator Plan for JAHUMS: A helicopter condition monitoring system most critical mission is to improve readiness and save crew's life, also it should be an efficient near real time on-line system. To meet these requirements, JAHUMS operational system employs novelty detection, to discriminate nominal/anomalous condition of a helicopter, which is a necessary requisite of fault diagnosis. This nominal/anomalous diagnosis initiates with discrimination analysis that produces normalized signatures suitable for transforming into dimensionless standardized statistical score elements, these elements can be individually fused into a feature vector.

To this purpose, the vibration data from seventeen sub-assemblies in the helicopter gearbox system are monitored. Each sub-assembly is paired with a single accelerometer, which is located at different locations on the gearboxes. In other words, conditions of crucial components such as, bearings and gears are being monitored by a single accelerometer mounted on a single sub-assembly. Whereas, only nine non-commensurate sensors are employed to monitor conditions of the gearbox system, meaning a single non-commensurate sensor will simultaneously monitor several sub-assemblies. Therefore, each accelerometer's vibration data contains signature information unique to its paired gearbox sub-assembly, while the same gearbox's non-commensurate data such as transmission oil temperature, oil pressure, and chip presence will include signature information common to the entire gearbox assembly. Table I summarizes a list of candidate components to be monitored.

Table I. Vibration Signal Sources from the Components Allocated in Sub-Assembly

Sub-Assembly	Components To Be Monitored		
	Bearings	**Gears**	**Gearbox Operating Condition**
Sub-Assy 1 (MGB: Port Ring)	Planet Carrier Sphr Roller 1, 2, 3, 4, and 5	Sun Gear; Planet Spur Gears; Ring Gear Planetary Assy.	Chip Input MDL LH Chip Input MDL RH Chip Main MDL Sump Oil Temperature Oil Pressure
Sub-Assy 2 (MGB: Stbd Ring)	Planet Carrier Sphr Roller 1, 2, 3, 4, and 5; 4th Hydraulic Pump Thrust, and Pump Preload	Sun Gear; Planet Spur Gears; Ring Gear Planetary Assy.	
Sub-Assy 3 (MGB: Stbd Main)	Stbd Main Bevel Pinion, and Pinion Roller; 4th Hydraulic Pump Thrust, and Pump preload	Main Bevel Gear	
Sub-Assy 4 (MGB: Port Main)	Port Main Bevel Pinion, and Pinion Roller; 4th Hydraulic Pump Thrust, and Pump preload	Main Bevel Gear	
Sub-Assy 5 (MGB: Port Input)	Port Input Pinion Roller, Ball, and INBC Roller; Port Input Gear Roller, and DBL; Port FWU Ball Input, Input Ball, and Output Ball; Port Gen Drive Ball; Port Hydraulic DR	Input Spiral Bevel Pinion, and Bevel Gear; Freewheel Spiral Bevel; Acc. Drive Bevel Pinion; Gen Spur Gear; Hyd Pump Spur Gear; Main Spiral Bevel Pinion	
Sub-Assy 6 (MGB: TTO Rad)	Main Rotor Roller, Timken Preload, and Timken Thrust; Main Rotor Swash Plate Bearing; Tail Take Thrust; Tail Take off Preload	Main Bevel Gear; TTO Main Bevel Gear; TTO Pinion Spiral Bevel Gear	
Sub-Assy 7 (MGB: Stbd Input)	Input Pinion Roller, Ball, and INBC Roller; Input Gear Roller, and DBL; FWU Ball Input, Input Ball, and Output Ball; Gen Drive Ball; Hydraulic DR	Input Spiral Bevel Pinion, and Gear; Freewheel Spiral Bevel; Acc. Drive Bevel Pinion; Gen Spur Gear; Hyd Pump Spur Gear; Main Spiral Bevel Pinion	
Sub-Assy 8	Hanger Bearing No. 1	N/A	Chip-Detection Oil Temperature
Sub-Assy 9	Hanger Bearing No. 2	N/A	
Sub-Assy 10	Hanger Bearing No. 3	N/A	
Sub-Assy 11	Hanger Bearing No.4	N/A	
Sub-Assy 12	Pillow Block Bearing	N/A	
Sub-Assy 13	Pylon Shaft Bearing	N/A	
Sub-Assy 14 (IGB: IGB Input)	IGB Input Thrust IGB Input Preload	Input Pinion Bevel Gear; Output Bevel Gear	
Sub-Assy 15 (IGB: IGB Output)	IGB Output Thrust IGB Output Preload	Input Pinion Bevel Gear; Output Bevel Gear	
Sub-Assy 16 (TGB: TGB Input)	TGB Input Thrust TGB Input Preload	Input Pinion Bevel Gear; Output Bevel Gear	Chip-Detection Oil Temperature
Sub-Assy 17 (TGB: TGB Output)	TGB Output Thrust TGB Output Preload	Input Pinion Bevel Gear; Output Bevel Gear	

The vibration signal of each sub-assembly and paired non-commensurate data will go through the feature extraction process using various diagnostic techniques to extract operational condition information on bearings, gears, and overall operating condition. The features from vibration and non-commensurate data are fused to form a feature vector,

which comprehensively represents SH-60 helicopter gearbox operational condition, thereby providing a more reliable and improved HUMS system. The overall schematic diagram for nominal and anomalous diagnostics of SH-60 helicopter gearboxes is illustrated in Figure 1.

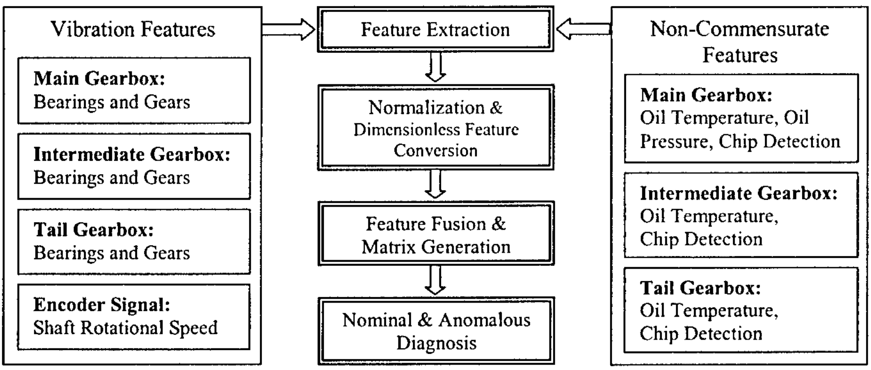


Figure 1. Overall Schematic Diagram for Nominal/Anomalous Diagnostic System

Information from a single accelerometer and non-commensurate sensors generate a feature matrix denoted by $\mathbf{FV}(i)_{m,n}$, comprised of a hundred feature vectors. An index i in the parenthesis denotes a sub-assembly or accelerometer number. A set of raw accelerometer data will be segmented into one hundred segments of equal length, and each segment is utilized to generate a row feature vector $\mathbf{FV}_m$ by using various nominal/anomalous diagnostic discrimination techniques, including statistics, DSP, frequency spectrum analysis, and classification from vibration and non-commensurate data. Therefore, there will be a hundred feature vectors collected into a feature matrix that has a dimension of 100 by 100 (Figure 2). To evaluate the condition of the entire SH-60 helicopter gearboxes, the same processes will be executed on all the 17 sub-assemblies of the SH-60 drive train.

Data Conditioning Process and Feature Vector Generation: Diagnostic algorithms are customized to each gearbox component to be analyzed. For a gear nominal/anomalous discriminator, synchronous averaging technique will be employed. In the averaging process, in-phase components will add together while the rest of the signal components will gradually cancel because of their random or non-synchronous relative phases. Therefore, the background extraneous noise and vibrations from other shafts and gears will be canceled because they are not phase synchronized an attenuate as the number of averages increase. Synchronous averaged signals initiates the gear nominal/anomalous discrimination analysis. Likewise, envelope analysis is utilized for bearing nominal/anomalous discrimination to diagnose rolling element bearing faults.

While vibration data analysis provides detailed gearbox components signature, non-commensurate chip detector data gives overall operating conditions of the gearbox that

can be characterized as fault or nominal. The gearbox operating condition discriminator module identifies the gearbox's operating condition as nominal or anomalous. Table II summarizes a list of various analysis techniques used by each nominal and anomalous discriminator module.

{Feature Matrix}=

$$FV(i)_{m,n} = \left\{ \begin{array}{c} FV_1 \\ FV_2 \\ FV_3 \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ FV_m \end{array} \right\} = \left\{ \begin{array}{l} a_{1,1}\ a_{1,2}\ a_{1,3}\ a_{1,4}\ a_{1,5}\ a_{1,6}\ a_{1,7} \cdots\cdots\cdots a_{1,96}\ a_{1,97}\ a_{1,98}\ a_{1,99}\ a_{1,n} \\ a_{2,1}\ a_{2,2}\ a_{2,3}\ a_{2,4}\ a_{2,5}\ a_{2,6}\ a_{2,7} \cdots\cdots\cdots a_{2,96}\ a_{2,97}\ a_{2,98}\ a_{2,99}\ a_{2,n} \\ a_{3,1}\ a_{3,2}\ a_{3,3}\ a_{3,4}\ a_{3,5}\ a_{3,6}\ a_{3,7} \cdots\cdots\cdots a_{3,96}\ a_{3,97}\ a_{3,98}\ a_{3,99}\ a_{3,n} \\ \qquad \cdot \qquad\quad \cdot \qquad\qquad\quad \cdot \\ \qquad \cdot \qquad\quad \cdot \qquad\qquad\quad \cdot \\ \qquad \cdot \qquad\quad \cdot \qquad\qquad\quad \cdot \\ \qquad \cdot \qquad\quad \cdot \qquad\qquad\quad \cdot \\ \qquad \cdot \qquad\quad \cdot \qquad\qquad\quad \cdot \\ a_{m,1}\ a_{m,2}\ a_{m,3}\ a_{m,4}\ a_{m,5}\ a_{m,6}\ a_{m,7} \cdots\cdots a_{m,96}\ a_{m,97}\ a_{m,98}\ a_{m,99}\ a_{m,n} \end{array} \right\}$$

Figure 2. Feature Matrix and Its Elements

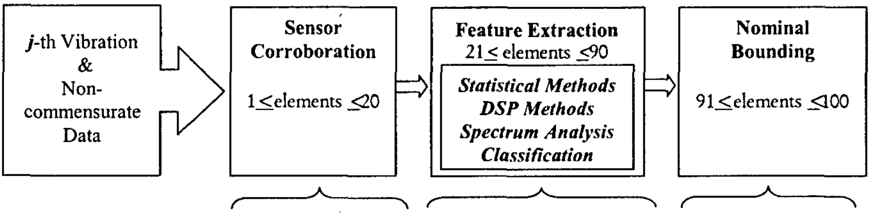
Table II. Nominal/Anomalous Diagnostic Analysis Techniques for Bearings and Gears

Component	Bearings	Gears	Operating Conditions
Detection Techniques	Skewness	Skewness	Classification
	Kurtosis	Kurtosis	
	Crest Factor	Fourth Root of Kurtosis	
	Impulse Factor	Impulse Factor	
	Clearance Factor	Clearance Factor	
	Shape Factor	Signal-std (RMS)	
	Signal-std (RMS)	Signal-pk-pk	
	Signal-pk-pk	Signal-pk	
	Envelope Band Energy (BE-std-n)	Peak ratio	
	Envelope Band Energy (BE-mean-n)	TEO-G	
	Envelop Band Kurtosis (BKv-n)	Rice Frequency	
	Energy in the base band (EB-n)	Harmonic Index	
	ORDI-n	SO1	
	IRDI-n	SO2	
	REDI-n	FM0	
	OREI-n	FM1	
	IREI-n	FM2A, FM2B	
	REEI-n	FM3	
	Peak Ratio	FM4A, FM4B	
	RMS Ratio-A	NA4	
	RMS Ratio-B	1st Harmonic ratio	

Feature Vector Sets and Their Elements: To reduce the errors due to inadequacies in the sensory system it is essential to select the best combination of input parameters. This

technique is called feature extraction, and a collection of these feature elements is called a feature vector, which is comprised of 100 elements.

This feature vector can be partitioned into three main categories; time invariant, time variant, and nominal bounding. A feature vector and its composition of elements is described in Figure 3.



$$FV_j = \{a_{j,1}\ a_{j,2} \cdots\cdots a_{j,20}\ a_{j,21}\ a_{j,22} \cdots\cdots a_{j,90}\ \ a_{j,91} \cdots\cdots a_{j,100}\}$$

Figure 3. Feature Vector and Its Elements Generation from Modules

Time invariant feature elements ($a_{k,21}$ to $a_{k,90}$), are generated during raw accelerometer signal qualification, and consist of four major parts; sensor corroboration, rotational stability, randomness verification, and stationarity validation, which are necessary to validate correct sensor operation, to correct variations in shaft speed, to confirm data quality. An invalid accelerometer performance may cause misdiagnosis of the gearbox condition. Therefore, prior to using a series of data collected from an SH-60 mission, every accelerometer's performance must be corroborated to determine if their dynamic range is acceptable to support its successful analysis. If a sensor fails this time invariant analysis, the respective data from an accelerometer is discarded and corrective action will be taken.

Once the sensor performance is corroborated, the time variant feature elements, $a_{k,l}$ where $l = 21$ to 90, known as nominal/anomalous discriminant features, will be generated by using analysis techniques listed in Table 2. Discriminants extracted during machinery diagnostic analysis usually describe some specific local waveform property of the machinery's operational health. These discriminants are usually in spectral, time or amplitude domain and are of the dimensional variety. The SH-60 Seahawk helicopter drive train components are comprised of various gears and bearings. Conditions on bearings and gears, along with overall gearbox operating conditions are characterized by vibration, gearbox oil temperature, pressure, and wear debris signatures. The nominal/anomalous discriminator is composed of three major analysis algorithm modules, which are respectively bearings, gears, and overall internal gearbox condition nominal/anomalous discriminator algorithms (Figure 4).

This analysis should be conducted intra-dependently because signals generated by bearings are of different waveform and characteristics than that produced by gears and other non-commensurate data. The characteristic of gear vibration is its synchronicity of multiples of shaft rotational speed known as shaft order; therefore, a gear nominal/anomalous discriminator must be capable of isolating the gear components from all others. On the

other hand, bearings have been difficult to monitor due to its low energy distribution masked by extraneous noise from many sources. In order to detect bearing anomalies effectively, pre-signal processing techniques, known by either the term Enveloping or Demodulation, has to be employed. The gearbox operating condition discriminator module uses non-commensurate data to identify overall gearbox condition using detailed information such as oil temperature, pressure, and debris presence in MGB, IGB, and TGB.

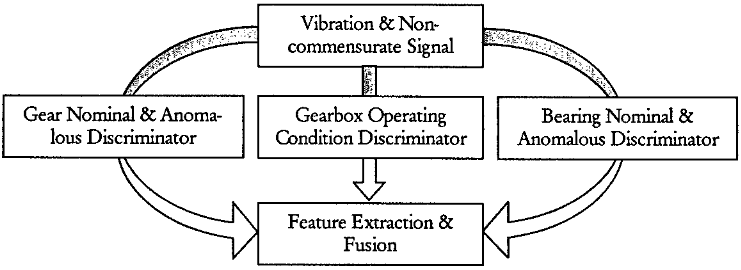


Figure 4. Nominal/Anomalous Diagnostic Discriminator Algorithm Structure

The final set of elements ($a_{k,l}$ where l =91 to 100) are generated that bound the classification of the helicopter drive train nominal operation. Nominal bounding shows how the nominal operational performance for drive train components can be bounded across the test group population of SH-60 helicopters. Magnitude and phase of the feature vector are calculated, and converted into standard statistical scores. All subsequent data can be statistically tested for its significance against the baseline to bound nominal operation for the population of SH-60 helicopters across the spectrum of their flight regime. Any subsequent anomalous data that is tested against these nominal criteria will be outside the acceptance region and will be classified as anomalous.

Nominal/Anomalous Diagnostic System and Its Benefits:

1. Dimensionless and normalized feature elements

Results from feature extraction techniques are not very useful when we want to make general comparisons across all fleets since an output level might not be the same from feature extraction to feature extraction, and helicopter to helicopter. Utilization of feature extracted outputs for comparison across two or more helicopters simply does not work if, as is usually the case, the helicopters have different running condition. Therefore, there is a need for global dimensionless discriminants that indicate the overall health condition of gearbox under analysis relative to its position in the population. Therefore, this procedure standardizes each feature value across helicopters so that their respective positions in population distribution can be evaluated. One way is to transform the values into scores within a universal scale. Standard scores, also called z scores, do this; they describe the relative position of a single score in the population distribution of scores. The benefits of converting the raw values into z scores are: 1) the shape of the distribu-

tion of standard scores is identical to that of the original distribution of raw values, 2) the mean of the distribution of z scores will always equal to zero regardless of the value of the mean in the raw value distribution. Therefore, dimensionless diagnostic discriminants' superiority to dimensional discriminants is predicated on their insensitiveness to amplitude and scale variations from helicopter to helicopter.

All feature vector element statistical scores will be sent to novelty detection diagnostic discriminator to make the final decision, nominal or anomalous. Additionally, these standardized scores known range afford significant data compression without loss of intelligence, to optimally diagnose the target machine's operating health.

2. Data compression

The resulting outputs from novelty detection diagnostic algorithms is transformed into statistical measures, which are of normalized and dimensionless statistical standard scores that provide relative positioning in the normal distribution yet retain individualized measurement scale, which results in significant data compression. Benefits of data compression are fast and efficient data calculation and reduced memory space, thus the system is able to be a real time and on-line system.

3. Data fusion

Normalized and dimensionless signature features enable the fusion of different characteristics such as vibration data and non-commensurate data. The major benefit from incorporating the non-commensurate data into nominal/anomalous features for the helicopter diagnostic system is to provide improved diagnoses capability and to reduce false alarms, thereby providing better diagnosis performance and improved helicopter operational health monitoring. For example, there may be instances where one analysis type indicates a fault while another has a contra indication, which is important because any abnormal condition indicators cause catastrophic failures. Another benefit from the implementation of data fusion is ability to simplify gauge display. Therefore, utilization of merged signatures increases diagnostic capabilities and results in less machinery mechanical trouble shooting.

Conclusion: JAHUMS must be highly reliable, and minimize false alarms. In order to achieve this goal, an advanced dynamic machinery health monitoring system that transforms of features extracted from raw data into normalized and dimensionless feature elements, has consistent output level via normalized dimensionless features, and standardize ranges regardless of different helicopter operational states of varying torque or load conditions. Implementation of significant data compression, utilization of data fusion, and integration of these two technique for the novelty detection of helicopter operational health monitoring provides an advanced, reliable, efficient, and robust diagnosis and prognosis system for both the military and commercial field. Also, this system gives sufficient warning to prevent catastrophic failures and a high utilization rate for helicopter availability, while operating in real time.

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